Mining and Understanding Stories in Text Sequences with Narrative Visualization

Award for Innovative Narrative Visualization and Analysis Methodology

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ABSTRACT

This paper presents our visual solution for *2021 VAST Min Challenge 3*. The core idea is to leverage the powerful interaction and storytelling capabilities of visualization to help analysts explore and understand the stories contained in text sequences. The visual solution consists of three tightly coupled narrative visual analysis systems that follow a top-down design approach. They allow analysts to eliminate noise data and progressively structure stories from coarse- to fine-grained into a series of semantically clear and independent narrative units, such as key events and plots. These narrative units not only serve as evidence to answer detailed questions, but also form a narrative visualization that charts the evolution of the story. Flexible and rich interactions support cue-based reasoning and verification, making the identification and creation of these narrative units more efficient and reliable. The three systems combine a variety of narrative visualization techniques, such as timeline, themeriver, samll multiples etc. Our visual solution led to the *Award for Innovative Narrative Visualization and Analysis Methodology*.

Index Terms: Text Sequences, Narrative Visualization, Storytelling

1 INTRODUCTION

Due to the strong potential in storytelling and interaction, visualization is often used to explore and understand stories in time-stamped text sequences [1]. The prerequisite for creating an effective narrative visualization is to extract a set of narrative units, such as key events and plots. However, two difficulties arise in this process: Text sequences are often filled with noise that is irrelevant to events; the semantics of each narrative unit must be clear and independent, with a granularity that matches the target information.

2021 VAST Min Challenge 3 provides two datasets: 3,872 messages posted by citizens and 191 text transcripts of emergency dispatches by police and fire departments. The questions require us to classify messages and identify the feature of each class(Q1), analyze the evolution of the risk(Q2), and determine a dispatch location for first responders(Q3). The first two questions correspond to the two difficulties mentioned above. Q1 requires separating event-related messages from event-unrelated messages. Q2 requires further dividing event-related messages into unit events to provide a sufficiently refined basis for analysis. Therefore, we developed three tightly coupled visual analysis systems(Fig.1). In the first system, the analyst manually classifies messages into event-related and event-unrelated classes according to a one-to-many relationship between the class and the author. In the second system, the analyst further classifies the event-related messages into three main events by labeling messages in a semantic map and then training a classifier. In the third system, the analyst interactively identifies and creates unit events for each main event based on the cues. For Q3, we developed an independent visualization(Fig.6) that implies possible connections between events.

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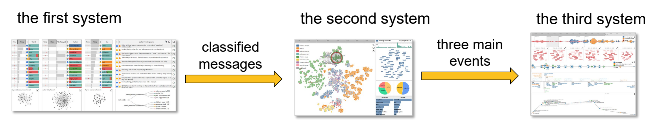

Figure 1: Our three tightly coupled visual analysis systems.

Figure 2: The first system: classify messages.

2 VISUAL SOLUTION

Fig.2 shows our first system. It consists of three parts: the list and network of top instances of keyword, author, and tag and a message list presenting the messages of a selected instance. We found a clear and reliable one-to-many relationship between the class and the author. For example, all messages published by KronosQuoth are chicken soup, and AbilaPost, Homelandllumination, KronosStar are media. Therefore, the analyst can classify messages(Q1) by manually labeling the author. We formalize this manual labeling process to create a classification tree. The analyst builds the tree from top to bottom by creating new classes(nodes) and assigning the messages of each top author to the existing classes.

Fig.3 shows our second system. In the left message map, messages with similar semantics are placed at approximate positions. The analyst can create a lens of arbitrary size and move it around in the message map. The feature words of the messages covered by the lens are listed on the left of the lens. Using the lens, analysts can check the semantics of any area of the map. Further, we can detect event-related messages and split them into several main events by first labeling their samples as a training set and then training and applying a classifier. The feature checker on the right displays various features of a class(Q1), including: forwarded times pre message, feature words, sentiment distribution, etc.

Fig.4 shows our third system. It is a top-down human-led narrative

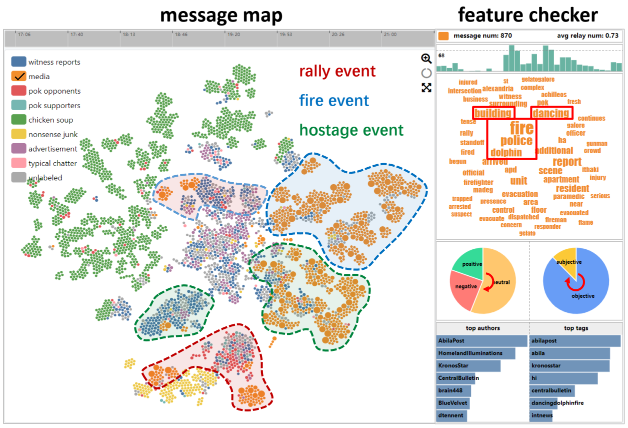

Figure 3: The second system: verify the classification, identify the feature of each class, and determine the message of main events.

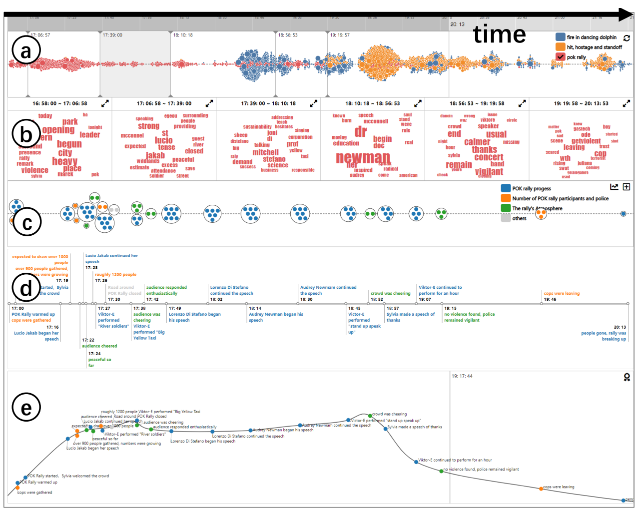

Figure 4: The third system: analyze the evolution of the risk.

visualization creation system. The horizontal direction of all views represents time. ⓐ represents the migration of the risk by showing the wax and wane of the main events. Small multiples in ⓑ represent feature words of the time periods created by the analyst. These feature words serve as clues to potential unit events. The analyst first identify and confirm a unit event by checking the messages related to a feature word, and then selects several representative messages as evidence to create the unit event. After creating a series of unit events in ⓒ, a timeline that explicitly displays the names of the unit events can be created in ⓓ with a simple click. At this point, the analyst can assess the level of risk and the number of people affected based on these unit events(Q2). The assessment results are recorded in a risk trend curve that is manually drawn by the analyst (ⓔ). The higher the y-value, the higher the risk.

3 Results

The lower right corner of Fig.2 presents a two-layer classification tree built after labeling the top 30 authors. The first layer includes two classes: the event-related class and the event-unrelated class. Each class includes four subclasses, e.g., witness report, media, chicken soup, advertisement, etc. As shown in the lower left corner of Fig.2, the three communities in the keyword co-occurrence network indicate three main events: rally event, fire event, and hostage

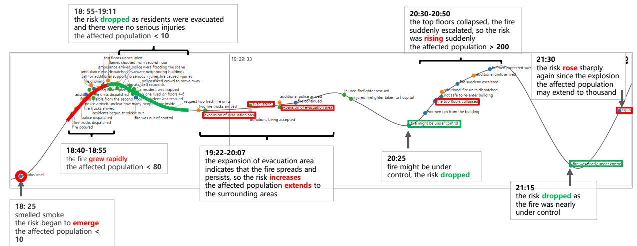

Figure 5: An example risk trend curve of the fire event.

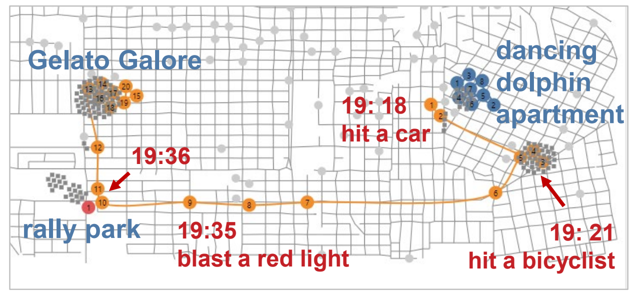

Figure 6: The escape route of the bad guys.

event. These events are further confirmed in the message map(Fig.3). The feature map reveals that the media mainly focused on the fire event and preferred to use neutral language for objective description.

Fig.5 shows the created risk trend curve of the fire event. At 18:25, a few residents smelled smoke. The risk began to emerge and the number of people affected was no more than 10. Between 18:40 and 18:55, the fire grew rapidly, so the risk and number of people affected increased rapidly. We suspect that fewer than 80 people were affected. Between 18:55 and 19:11, with the evacuation of the apartment, we believe the risk of fatalities was decreasing and that the number of people affected was unchanged. Since then, the risk fluctuated significantly for many times. People affected ranged from less than 80 apartment residents to more than 200 nearby residents and store owners, and may eventually extended to thousands of people throughout the street.

As shown in Fig.6, the bad guys were first seen near the burning apartment. It was 19:18, and they hit a car. Meanwhile, the fire was spreading and police were expanding the evacuation area. So, we suspect that the bad guys were hiding in or near the burning apartment and were forced to flee with their hostages by the fire and the police. This indicates that the hostage event may not happen without the fire event. So, from the perspective of retrospective analysis, we will send first responders to the bruning apartment(Q3).

4 Conclusion

We presented our visual solution for *2021 VAST Min Challenge 3*. It is a top-down workflow that asks the analyst to gradually identify and create narrative units with clear and independent semantics. In this process, the analyst removes noise data, masters the details of the story, and finally presents the analysis results in a narrative visualization. The idea of interactively creating a narrative visualization is worth trying, especially for the problem that the required abstract semantic structure cannot be derived from the algorithm.

References

[1] E. Segel and J. Heer. Narrative visualization: Telling stories with data. *IEEE transactions on visualization and computer graphics*, 16(6):1139–1148, 2010.